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Quantifying the effect of labor market size on learning externalities

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Abstract

We show for Germany that labor productivity as reflected in wage is, ceteris paribus, higher for workers who previously acquired work experience in rather urban labor markets with a large local workforce than in rather rural labor markets which are small in terms of regional employment. Our empirical analysis provides new evidence on the magnitude of these dynamic agglomeration gains by estimating the elasticity of wages with regard to the (cumulated) size of the local labor markets in which workers acquired experience. It shows that this elasticity increases with the level of individual experience to more than 0.06 implying that today's wage of a worker with 20 years of experience or more would be about four to five percent higher if the worker would have gained all his or her experience in local labor markets double the size of the labor markets in which he or she actually was working in the past. These identified dynamic agglomeration gains are supposed to be related to learning externalities. The analysis uses information on individual employment biographies and regional employment from 1975 onwards. The wage information refers to more than 300,000 entry wages of new employment relationships in Germany in the period 2005 to 2011. The depreciation of human capital is taken into account and that high-skilled workers presumably are the ones other workers learn the most from.

Zusammenfassung

Mit dieser Studie zeigen wir für Deutschland, dass der heutige Arbeitslohn einer Person, ein Indikator für die individuelle Arbeitsproduktivität, unabhängig davon, wo eine Person heute tätig ist, ceteris paribus signifikant höher ist, wenn die Person in der Vergangenheit Arbeitserfahrung in großen, also eher städtischen statt in kleinen, eher ländlichen Arbeitsmärkten gesammelt hat, wobei wir die Arbeitsmarktgröße anhand der Beschäftigtenzahl messen. Die vorliegende Arbeit liefert neue Erkenntnisse über die Größe dieser dynamischen Agglomerationsvorteile, die mutmaßlich auf Lernexternalitäten in großen Arbeitsmärkten zurückzuführen sind. Es wird die Elastizität individueller Löhne hinsichtlich der (kumulierten) Größe der regionalen Arbeitsmärke geschätzt, in denen zuvor Arbeitserfahrung gesammelt wurde. Ein zentrales Ergebnis ist, dass diese Elastizität im Erwerbsverlauf mit der Dauer vorheriger Beschäftigungszeiten bis zu einem Niveau von über 0,06 ansteigt. Folglich wäre der individuelle Lohn einer Arbeitskraft mit 20 Jahren Arbeitserfahrung oder mehr heute um vier bis fünf Prozent höher, hätte die Person die Arbeitserfahrung in regionalen Arbeitsmärkten gesammelt, die doppelt so groß hinsichtlich lokaler Beschäftigung gewesen wären wie die Arbeitsmärkte, in denen die Person tatsächlich gearbeitet hat. Die Analyse beruht auf Informationen zu individuellen Arbeitsmarktbiografien und regionaler Beschäftigung in Deutschland ab 1975. Die Lohninformation bezieht sich auf Löhne, die zu Beginn von mehr als 300.000 im Zeitraum 2005 bis 2011 begonnenen neuen Beschäftigungsverhätnissen in Deutschland gezahlt wurden. Es wird berücksichtigt, dass erworbene Kenntnisse und Fähigkeiten im Zeitverlauf an Wert verlieren und dass Arbeitskräfte mutmaßlich insbesondere von hochqualifizierten Personen lernen.

JEL classification: R10, R23, J31

Keywords: Dynamic agglomeration economies, Human capital externalities, Learning, Regional disparities

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1 Introduction

There is extensive empirical evidence that the nominal wage level in a local labor market is positively correlated with the size of the local workforce in terms of total regional employment. Conditional on the wage differential between East and West Germany, we estimate a corresponding raw elasticity for Germany of about 0.08. Similar significant disparities are observed for other countries; see, e.g., Glaeser/Maré (2001) for the United States and Combes/Duranton/Gobillon (2008) for France. The question as to why firms in large agglomerated labor markets[1] pay high wages than in small rural labor markets and do not relocate to the latter regions in which labor is cheaper has attracted attention for a long time.[2]

As Glaeser/Maré put it, “The best explanation [...] is that these higher wages are compensated for by higher productivity.” (Glaeser/Maré, 2001: 317). They distinguish three possible explanations as to why workers might be more productive in urban than in non-urban labor markets: sorting as well as static and dynamic agglomeration economies. Even though most of the underlying theoretical arguments were already discussed in the 19th century by List (1838), Roscher (1878), and Marshall (1890), it is still an ongoing issue as to understand the mechanisms behind this phenomenon relates to the fundamental urban economics question about why cities exist (Glaeser/Maré, 2001).

The main interest of this paper is dynamic agglomeration economies which are supposed to enhance individual wage growth in cities.[3] Two underlying mechanisms are primarily discussed in this context. In 1838 Friedrich List had already recognized, inter alia, that a concentration of economic activity enhances the individual opportunities for workers to acquire new skills, and that accessibility helps them to find new jobs. These mechanisms are now labeled ‘learning’ and ‘coordination’, also referred to as ‘dynamic matching’. Similar to List’s considerations, the coordination hypothesis suggests that urban density makes it “easier for workers to find the best jobs for themselves” (Glaeser/Maré, 2001: 322). The learning hypothesis proposes cities create learning opportunities for everyday people since the opportunities to acquire new skills increase with the rate of new contacts between individuals and this is highest in a dense urban environment (Glaeser, 1999). Furthermore, given that the latest technologies are used especially in innovative, densely populated areas, workers there particularly become familiar with them (List, 1838).

As also discussed by Wheeler (2006) and Yankow (2006), the accumulation of more human capital in an agglomerated urban environment should result in a higher wage even if a worker migrates to another (rural) labor market, meaning that the value of work experience is significantly determined by the location in which it was acquired. Pioneered by the work of De La Roca/Puga (2017), recent studies therefore analyze wages of indi-

[1] We use terms like ’agglomeration’, ’city’, ’urban region’, ’large local labor market’ interchangeably to improve readability. ’Labor market size’ refers to the size of a local labor market in terms of regional employment.

[2] Explanations why workers do not fully concentrate in cities where wages are higher refer to higher costs of living and urban disamenities (Glaeser/Maré, 2001).

[3] We refrain from providing a review of the literature on the importance of sorting and static agglomeration economies and refer to the comprehensive survey by Combes/Gobillon (2015). A meta-analysis of estimates of urban agglomeration economies is provided by Melo/Graham/Noland (2009).

vidual employment relationships in dependence of the locations in which the corresponding worker previously acquired experience (see also Andersson/Klaesson/Larsson, 2014; D'Costa/Overman, 2014; Matano/Naticchioni, 2016; Carlsen/Rattsø/Stokke, 2016). These studies show for different European countries that work experience which was acquired in the very largest cities of the considered country has a significantly higher value than experience acquired in the rest of the country and that this manifests in higher wages. We extend this literature by estimating the elasticity of wage with regard to the size of the local labor markets in which work experience was acquired using information on regional employment from 1975 onwards. When doing so, we distinguish workers according to their skill level taking into account that not all workers benefit equally from dynamic agglomeration gains as shown by previous studies. Furthermore, as previous papers focused on experience acquired in the largest cities of the considered country and do not look at the other end of the distribution, we test whether labor market size in terms of employment has to exceed a certain threshold such that the acquired work experience is rewarded with a wage premium by future employers.

The empirical setup takes into account that agglomeration gains based on learning externalities are supposed to depreciate over time just like the additionally acquired human capital. More precisely, we, in contrast to previous papers, also estimate the rate by which the relevance of the size of a labor market in which experience was acquired at some point in the past declines with time passed since that day. Thereby, we provide evidence that dynamic agglomeration gains converge towards an upper bound over working life, meaning that the productivity of a worker at the end of his or her career is only negligibly affected by the size of the labor markets in which the first years of experience were acquired. It indicates that the location of labor market entry does not have a direct effect on the productivity of a worker with several years of work experience, albeit the location of labor market entry likely affects the location in which experience was acquired in the subsequent years due to the rather low mobility of workers over their working lives. For example, at the median observation almost 80 percent of the work experience brought into the new employment relationship under investigation was acquired in the same local labor market in which the new employer is situated. Moreover, more than one third of the workers never left the region in which the respective first employer was located (see also Bosquet/Overman (2016) who analyze wages in dependence of the birthplaces of the respective workers).

Presuming that (highly) skilled workers are the ones from whom other workers learn the most, the question arises of whether dynamic agglomeration gains in general, and learning externalities in particular, stem from the large local workforce or from the typically above average share of high-skilled labor in agglomerated labor markets. Taking into account that a related strand of literature on the external effects of localized human capital discusses the role of local learning externalities as well (Heuermann/Halfdanarson/Suedekum, 2010), we ultimately distinguish the dynamic productivity effect of labor market size from the dynamic productivity effect of the local share of high-skilled labor.[4] Our findings suggest that high-skilled workers benefit more from acquiring experience in large labor markets than

[4] Comprehensive overviews of the literature on human capital externalities which focuses on the composition of the local workforce with respect to skills, rather than on labor market size are given by Moretti (2004b) and Duranton (2007).

less skilled workers since only the former benefit (additionally) from the above average share of high-skilled labor in the local labor market. Following Jovanovic/Rob (1989), one explanation is that especially the encounter of skilled workers with different ideas might generate new ideas and knowledge.

The basis of our empirical analysis is administrative data on individual employment biographies for Germany from the Institute for Employment Research (IAB). We are able to follow a worker's employment history back to 1975 and observe the size of all regional labor markets in Germany in which he or she acquired work experience. This information is used to estimate the elasticity of wage with regard to the size of the labor market in which previous work experience was acquired. The wage information refers to individual new employment relationships in Germany starting between 2005 and 2011. These wages contain important information as to how firms value work experience when they hire a worker depending on the size of the labor market in which it was acquired. By considering the wages associated with new employment relationships, we reduce the risk of an omitted variable bias since other factors, like professional development training offered by the firm, which are unobserved by the econometrician gain importance for productivity as tenure increases (Hamann/Niebuhr/Peters, 2016).

The identified dynamic agglomeration gains should be strongly related to learning externalities. We control for sorting of more able workers into large labor markets and static agglomeration benefits by means of individual as well as time-varying region-fixed effects. Furthermore, we include the number of previous employers in order to control for dynamic matching according to the coordination hypothesis. Time-varying individual characteristics and the individual labor market biographies of the workers are considered, as well as time-varying characteristics of the local industry.

The remainder of the paper is structured as follows. In Section 2 we describe the strategy of our empirical analysis and in Section 3 the data at hand. In Section 4 we discuss the results of our empirical analysis and finally, in Section 5 we set out our conclusions.

2 Empirical strategy

2.1 Baseline specification

In order to quantify the benefit of acquiring work experience in large local labor markets, we analyze the wages associated with new employment relationships after transitions to employment. These wages contain important information on how firms value previously acquired work experience when they hire a new employee. As tenure increases, other factors, like on-the-job and professional development training offered by the firm, which are unobserved by the econometrician, will gain importance for productivity (Hamann/Niebuhr/Peters, 2016). Hence, considering the wage of newly established employment relationships reduces the risk of an omitted variable bias.

In our analysis, we make use of a micro-econometric framework the various specifications of which are discussed in detail by Combes/Gobillon (2015). The empirical strategy is in the same spirit as the models estimated by De La Roca/Puga (2017) and in related studies where wages are analyzed in dependence of specific cities in which a worker previously acquired work experience. We are interested in the general relationship between dynamic productivity gains and the size of the labor markets in which experience was acquired rather than in the specific wage premium paid for experience acquired in a certain (very large) city. Therefore, we refrain from estimating the value of city-specific experience for a few selected cities as previous studies have done, but apply an estimation strategy that allows general conclusions on the magnitude of dynamic agglomeration economies which presumably are based on learning externalities.[5]

Suppose a worker i is hired by an establishment at day t and the logarithm of the wage which the worker receives, $w_{i,t}$, is given by Equation (1).

$$w_{i,t} = u_i + \mu_{r(i,t),y(t)} + \underbrace{\sum_{\tau=1}^{t-1} (1-\theta)^{t-\tau-1} I(O_{i,\tau}=1) \nu_{r(i,\tau),\tau}}_{Q_{i,t}} + \mathbf{x}'_{i,t}\beta + \varepsilon_{i,t} \tag{1}$$

u_i denotes an individual fixed effect and $\mu_{r,y}$ a fixed effect for local labor market r, i.e., the labor market individual i starts to work on date t. These fixed effects are allowed to vary across years y. $Q_{i,t}$ denotes the wage premium that worker i receives for the work experience he or she acquired until $t-1$, $\mathbf{x}_{i,t}$ is a vector of time-varying individual characteristics with parameter vector β, and $\varepsilon_{i,t}$ is an error term. In the empirical analysis subscript t refers to days between January 1, 2005 and December 31, 2011 and $\tau = 1$ to January 1, 1975.

The worker fixed effect captures all unobserved time-invariant characteristics of the considered worker that determine the individual wage. The region-year fixed effect refers to the region-specific productivity level that is based on static local effects which may vary over time. Dynamic local effects are captured by $Q_{i,t}$, where $O_{i,\tau}$ is a dummy variable taking the value 1 if individual i was working[6] in the past at day τ and 0 else, $\nu_{s,\tau}$ is a weight of the corresponding work experience depending on the local labor market in which it was acquired[7] at τ, and θ is a depreciation rate which is supposed to be in the interval $(0;1)$ taking into account that human capital which is acquired while working presumably loses in value the more time passes. The depreciation of human capital might be caused by, i.a., changes in the skills demanded for a particular job due to technological change, shifts in the demand for particular occupations due to changes in the industry structure, or the loss of certain knowledge and skills due to insufficient use (De Grip/Van Loo, 2002).

[5] Appendix B.2 contains the results that we obtain when estimating the baseline specification with dynamic agglomeration gains of De La Roca/Puga (2017) using German data. The results provide information on the wage premium that workers receive given they acquired experience in one of the largest German cities.

[6] Because information on self-employment is not available, we only consider spells of employment subject to social security contributions.

[7] Combes/Gobillon (2015) discuss that the value of work experience may also vary depending on the labor market in which the experience is used. The results by De La Roca/Puga (2017) indicate, however, that it is (primarily) the labor market in which experience was acquired that determine its value. Our additional estimations lead to the same conclusion (see Appendices B.2 and B.3). Therefore, we refrain in the description of the estimation strategy from adding an additional subscript $r(i,t)$ to parameter $\nu_{r(i,\tau),\tau}$.

In order to assess the magnitude of dynamic agglomeration economies, we assume that there is a log-linear relationship between net-agglomeration gains and local labor market size which we measure as did, e.g., Bosquet/Overman (2016), in terms of number of employees in the respective local labor market (travel-to-work area, see data description). More precisely, we assume that $v_{r,\tau}$ — the (logarithmic) value of work experience acquired at day τ valued at day $\tau+1$ — is given by Equation (2) which may be interpreted as a learning function capturing externalities of acquiring work experience in large local labor markets. $emp_{r,\tau}$ denotes the size of local labor market r at τ in terms of total regional employment subject to social security contribution.

$$v_{r,\tau} = \begin{cases} \delta \ln\left(\frac{emp_{r(i,\tau),\tau}}{\underline{emp}}\right) & \text{if } emp_{r(i,\tau),\tau} > \underline{emp} \\ 0 & \text{else} \end{cases} \tag{2}$$

$\delta \ln(emp_{r(i,\tau),\tau}/\underline{emp})$ is the value of the additional human capital valued at $\tau+1$ that a worker accumulates by working at date τ in a labor market with size $emp_{r,\tau}$, given it exceeds a certain (unknown) threshold $\underline{emp}$. The term $\ln(emp_{r(i,\tau),\tau}/\underline{emp})$ may be interpreted as local learning opportunities. In accordance with Duranton/Puga (2004), marginal learning benefits with regard to labor market size are assumed to be positive but decreasing. δ denotes the corresponding elasticity. If the local labor market is smaller than $\underline{emp}$, a worker does not acquire any human capital he or she can make use of in the future, meaning that the acquired experience is not rewarded by future employers with a wage premium. Hence, the introduction of $\underline{emp}$ enables us to test whether even work experience acquired in rural labor markets with a small local workforce boosts individual productivity.[8]

In order to obtain the baseline model of our empirical analysis, we rewrite the learning function such that it is given by:

$$v_{r,\tau} = \begin{cases} \gamma + \delta \ln(emp_{r(i,\tau),\tau}) & \text{if } emp_{r(i,\tau),\tau} > \underline{emp} \\ 0 & \text{else,} \end{cases} \tag{3}$$

with $\gamma \equiv -\delta \ln(\underline{emp})$. Since our focus is on estimating the effect of labor market size on the value of acquired work experience rather than quantifying the full set of parameters $v_{r,\tau}$, we replace $v_{r,\tau}$ in Equation (1) by this expression. Given that the labor market size is always larger than the unknown threshold,[9] inserting Equation (3) into Equation (1) leads to:

$$\begin{aligned} w_{i,t} \quad = \quad & u_i + \mu_{r(i,t),y(t)} + \gamma \sum_{\tau=1}^{t-1} (1-\theta)^{t-\tau-1} I(O_{i,\tau}=1) + \\ & + \delta \sum_{\tau=1}^{t-1} (1-\theta)^{t-\tau-1} I(O_{i,\tau}=1) \ln(emp_{r(i,\tau),\tau}) + \mathbf{x}'_{i,t}\beta + \varepsilon_{i,t}. \end{aligned} \tag{4}$$

Accordingly, the productivity of worker i at date t as reflected in the corresponding wage depends on the number of days i worked in the past and the size of the labor markets

8 We gratefully thank Johannes Bröcker for the suggestion to introduce $\underline{emp}$ in the learning function.

9 After estimating Equation (4) it has to be verified whether all local labor markets are indeed larger than $\widehat{\underline{emp}}$ which is given by $\exp(-\hat{\gamma}/\hat{\delta})$. If some local labor markets are smaller than $\widehat{\underline{emp}}$, the size of the respective labor market has to be set to the estimated threshold and an iterative procedure has to be applied in order to obtain the solution for Equation (2).

in which the work experience was acquired. Suppose the depreciation rate θ is zero, then $\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}I(O_{i,\tau}=1)$ equals the number of days individual i acquired work experience before day t as that term reduces to $\sum_{\tau=1}^{t-1}I(O_{i,\tau}=1)$. The term $\sum_{\tau=1}^{t-1}I(O_{i,\tau}=1)\ln(emp_{r(i,\tau),\tau})$ may be interpreted as i's total number of local learning opportunities until date $t-1$ depending on the size of the labor markets in which experience was acquired.

Equation (4) indicates that a one percent increase in the size of the labor market in which experience was acquired at day $t-1$ results in a wage increase of δ percent and a one percent increase in the size of the labor market in which experience was acquired at day $t-\tau$ in a wage increase of $\delta(1-\theta)^{\tau-1}$ percent, addressing that the value of the human capital acquired at $t-\tau$ declined each day after acquisition by rate θ. If all labor markets individual i was working in before t would have been one percent larger, the productivity at day t would be $\delta\sum_{\tau=1}^{t-1}(1-\theta)^{t-\tau-1}$ percent higher. It takes into account that having recently benefited from acquiring experience in a large labor market increases todays productivity stronger than agglomeration economies experienced years ago given that acquired human capital depreciates. The crucial parameter is θ. The larger θ is, the relatively larger is the productivity effect of the size of the labor markets in which recent experience was acquired.

2.2 The interaction of labor market size and skills

Taking into account the interaction of labor market size and skills, we on the one hand let the parameters γ, δ, and θ vary across skill groups $s(i)$, see Equation (5). Similarly to Carlsen/Rattsø/Stokke (2016), we use information on the individual educational level to distinguish university graduates (high-skilled workers) from all other (non-high-skilled) workers. Thereby, we take into account that workers with high abilities / high skills / a low share of non-routine job tasks benefit more from acquiring experience in large labor markets than do others as shown by De La Roca/Puga (2017), Carlsen/Rattsø/Stokke (2016), and Andersson/Klaesson/Larsson (2014), respectively. Hence, we obtain skill-specific elasticities of wage with regard to the size of the labor market in which experience was acquired $\delta_{s(i)}$.

$$\begin{aligned} w_{i,t} &= u_i+\mu_{r(i,t),y(t)}+\gamma_{s(i)}\sum_{\tau=1}^{t-1}(1-\theta_{s(i)})^{t-\tau-1}I(O_{i,\tau}=1)+ \\ &\quad +\delta_{s(i)}\sum_{\tau=1}^{t-1}(1-\theta_{s(i)})^{t-\tau-1}I(O_{i,\tau}=1)\ln(emp_{r(i,\tau),\tau})+\mathbf{x}'_{i,t}\beta+\varepsilon_{i,t} \end{aligned} \quad (5)$$

On the other hand, we consider not only the size of the labor markets in which a worker acquired work experience in terms of total regional employment in the regression analysis, but also the skill structure of the respective local labor forces. Typically, large urbanized labor markets are not only characterized by a large number of workers but also by an above average share of high-skilled labor. In accordance with the literature on human capital externalities, presumably especially the highly skilled workers are the workers from whom others learn the most. An important question therefore is to which extent dynamic agglomeration gains can be explained by the higher share of high-skilled labor. In order to provide corresponding insights, we add the (logarithmic) share of workers with a university degree in total regional employment, $hskill_{s,\tau}/emp_{s,\tau}$, as a further explanatory variably referring to the local labor market in which individual i acquired work experience at day τ such that the regression model is given by:

$$\begin{aligned} w_{i,t} \quad = \quad & u_i + \mu_{r(i,t),y(t)} + \gamma_{s(i)} \sum_{\tau=1}^{t-1} (1-\theta_{s(i)})^{t-\tau-1} I(O_{i,\tau}=1) + \\ & + \delta_{s(i)} \sum_{\tau=1}^{t-1} (1-\theta_{s(i)})^{t-\tau-1} I(O_{i,\tau}=1) \ln(emp_{r(i,\tau),\tau}) + \\ & + \rho_{s(i)} \sum_{\tau=1}^{t-1} (1-\theta_{s(i)})^{t-\tau-1} I(O_{i,\tau}=1) \ln\left(\frac{hskill_{r(i,\tau),\tau}}{emp_{r(i,\tau),\tau}}\right) + \mathbf{x}'_{i,t}\beta + \varepsilon_{i,t}. \end{aligned} \tag{6}$$

Estimating Equation (6), $\delta_{s(i)}$ refers only to the isolated benefit of acquiring experience in a labor market with a large workforce in terms of total regional employment. It does not capture the benefit of acquiring experience in a labor market with an above average share of high-skilled labor any longer. This latter benefit is now captured by elasticity $\rho_{s(i)}$. Since the relevance of local high-skilled labor may differ across skill-groups, the parameters are again allowed to vary accordingly. It should be noted that γ refers in this specification not only to the (unknown) minimum number of workers, but also to an (unknown) minimum share of high-skilled labor that has to be exceeded such that learning externalities arise, denoted by $\underline{emp}$ and $\underline{hskill/emp}$, respectively: $\gamma \equiv -\delta \ln(\underline{emp}) - \rho \ln(\underline{hskill/emp})$.

2.3 Econometric issues

Since the regression models (4) to (6) are highly non-linear in θ, the Gauss-Newton-Algorithm is applied to find the least squares estimators of the parameters. As discussed by Combes/Duranton/Gobillon (2011) in detail, endogeneity has to be taken into account when analyzing the impact of labor market size on wages. The risk of biased estimates due to omitted variables should be reduced by the setup of our empirical analysis. We control for all time-invariant characteristics of the worker by means of individual fixed effects as well as for time-varying characteristics like educational degree and pre-employment status. We also aim at controlling for the second potential channel of dynamic agglomeration benefits, dynamic matching, since we are in particular interested in the magnitude of learning externalities. Therefore, we consider the number of previous employers as additional control variable.[10]

At the regional level we use region-year fixed effects to control for all time-variant and time-invariant characteristics of the local labor market that lead to static regional wage differentials. In addition, we consider observable characteristics of the local industry, skill specific local unemployment rates as well as industry fixed effects. The latter capture all time-invariant industry specific factors that have an impact on wages.

[10] Even though we control for various observable and unobservable characteristics of the workers, we cannot fully rule out that our analysis still suffers from selection effects. Imagine, e.g., workers have expectations on their individual learning opportunities in urban labor markets and took them into account when they decided where to work. This would imply a positive selection because especially those workers who expect to learn much would have decided to acquire experience in a large labor market. At least part of this selection should be captured by the individual fixed effects and by the time-variant individual characteristics like educational degree. However, if the expected individual learning opportunities depend on unobserved time-variant individual characteristics, the estimated benefits of acquiring experience in large local labor markets are likely biased upwards.

Also the risk of reverse causality should be of minor concern here. The pivotal explanatory variable is the size of the labor markets in which an individual acquired experience *before* date t, not the size of the labor market at the date at which the analyzed wage is paid. Of course, the size of the labor market in which experience has been acquired and where it is used are likely significantly correlated. However, the included region-year fixed effects control for all characteristics of the region in which individual i works at date t, including its size.

As discussed, i.a., by Combes/Gobillon (2015), a second econometric issue that has to be discussed refers to the computation of standard errors. Moulton (1990) shows that it is important to account for cross-sectional correlation in the error terms if a model explains individual outcomes by characteristics of the regional environment. As matrix $\mathbf{x}_{i,t}$ contains, among other things, information on the local industry, the appropriate solution would be to cluster the standard errors at the local industry level. However, this is not possible as the model includes individual fixed effects and because workers are mobile between regions and industries. The standard errors that we report are clustered at individual level. They are robust with regard to heteroskedasticity and serial correlation in the error terms (Wooldridge, 2013). It is worth noting that we obtain very similar standard errors if we compute them as suggested by Driscoll/Kraay (1998). Those standard errors are robust to general forms of cross-sectional and serial dependence in the error terms (see also Hoechle, 2007).[11]

An alternative strategy would be to apply a two-step procedure in the same spirit as Combes/Duranton/Gobillon (2008) and De La Roca/Puga (2017), respectively. It requires the estimation of the full set of parameters $v_{r(i,\tau)}$ on the first step and on the second the regression of the estimated coefficients $\hat{v}_{r,\tau}$ on regional characteristics such as total regional employment $emp_{r,\tau}$ and the local share of high-skilled labor $hskill_{r,\tau}/emp_{r,\tau}$. However, as noted by Combes/Gobillon applying the two-step procedure, it is not possible to disentangle the dynamic agglomeration gain from "the evolution of static effects" (Combes/Gobillon, 2015: 265). Therefore, we refrain from the two-step estimation strategy.

3 Data and descriptive evidence

3.1 Individual data set

In order to quantify the impact of labor market size on the value of work experience, we analyze wages of 336,286 new employment relationships in Germany, starting within the period 2005 to 2011. The new employment relationships are identified using detailed information on individual labor market biographies. The latter also enables the observation of where and when work experience was acquired as well as information on the date and location of previous spells of employment.

The information on labor market biographies is taken from the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB). Among other information,

[11] The additional results are available from the authors upon request.

the IEB contains very reliable micro data on employment which comes from the integrated notification procedure for health, pension, and unemployment insurance.[12] The data at hand comprises a five percent random sample of all employees with at least one notification to social security between 2005 and 2011.

We exclude individuals if it is not possible to observe the full employment biography. The setup of our analysis requires information on all locations in which previous work experience was acquired.[13] Among others, we exclude all individuals born before 1960 because the IEB only contains information on employment from 1975 onwards. A detailed description is provided in Appendix A. For the remaining sample of workers our data set captures all spells of employment subject to social security contributions. We use them to identify transitions to employment within the period between 2005 and 2011 focusing on new full-time employment outside the public sector and outside of the temporary employment industry.[14] For the new employment relationships we observe the corresponding gross daily wage as well as further information on the new job (e.g., kind of occupation) and the worker (e.g., age, educational attainment, and sex). The wage information in the IEB is right censored as firms report earnings only up to the upper limit for social security contributions. Therefore, we partly impute the wages, see Appendix A.

Using information on all previous spells of employment, we compute the individual labor market experience at the date at which the new employment relationship starts. Moreover, we generate important control variables that provide information on the recent labor market biography with regard to the pre-employment status, length of non-employment before the transition to employment, unemployment benefits, and participation in measures of active labor market policy. The information is also taken from the IEB. Detailed information on all the variables that we use is provided by Table A.1 in Appendix A. Summary statistics can be found in Table A.2.

Descriptive statistics indicate that a large share of the considered new employment relationships refers to rather young workers with few years of labor market experience. One likely explanation is that workers change jobs more frequently when they are young to find the job they like most as noted by Wheeler (2008). The mean work experience in our data set amounts to about 9.4 years.

The establishment identifier in the IEB is used to identify the number of different establishments an individual worked at before the considered new employment relationship. We use this information as a control variable addressing the fact that frequent job changes are undertaken to improve the matching between firms and workers.[15] Additionally, the establishment identifier allows us to add important information on the establishment to the individual data set, e.g., location, industry, establishment size as well as skill and age structure

[12] For a more detailed description of the IEB see vom Berge/Burghardt/Trenkle (2013).

[13] The IEB does not contain information on the self-employed and civil servants. Therefore, our analysis is based on information on employment subject to social security contributions only.

[14] In order to apply fixed effects estimation, we furthermore exclude all individuals (about 200,000) for which we observe only one new employment relationship starting in the considered period. It has a negligible effect on the composition of the sample with regard to (observable) worker characteristics.

[15] Different units of one firm that are located in different municipalities are considered as independent establishments. It is not possible to identify whether different establishments belong to the same firm.

of the staff. The data is taken from the Establishment History Panel (BHP). We also merge information on the local industry as well as on skill specific local unemployment rates. We compute corresponding indicators based on data taken from the (un-)employment statistics of the Federal Employment Agency (FEA).

3.2 The size of local labor markets

For Italy, Di Addario/Patacchini (2008) show that the effect of population mass on wages declines rapidly with distance. They find a significant impact on wages for only a distance up to 12 kilometers. This indicates that agglomeration benefits depend on the immediate environment. Taking this into account and addressing that learning externalities are thought to crucially depend on interaction between individuals, we choose labor market regions as spatial units for our analysis. Their definition is taken from Kosfeld/Werner (2012), who define 141 regional labor market regions employing a factor analysis to German commuter structure between NUTS-3 regions. On average the labor market regions have a radius of about 27 km (see Table 1). Because the regions are supposed to represent integrated local labor markets, we assume that workers exchange knowledge exclusively within these regions.[16]

Table 1: The size of German labor market regions

	Local labor market size in terms of...		
	radius in km†	thousand employees‡	share of high-skilled labor§
Minimum	10.3	13.8	2.3
Median	26.0	110.8	6.0
Mean	27.0	179.1	7.0
Maximum	51.8	1206.5	20.0

N=141.

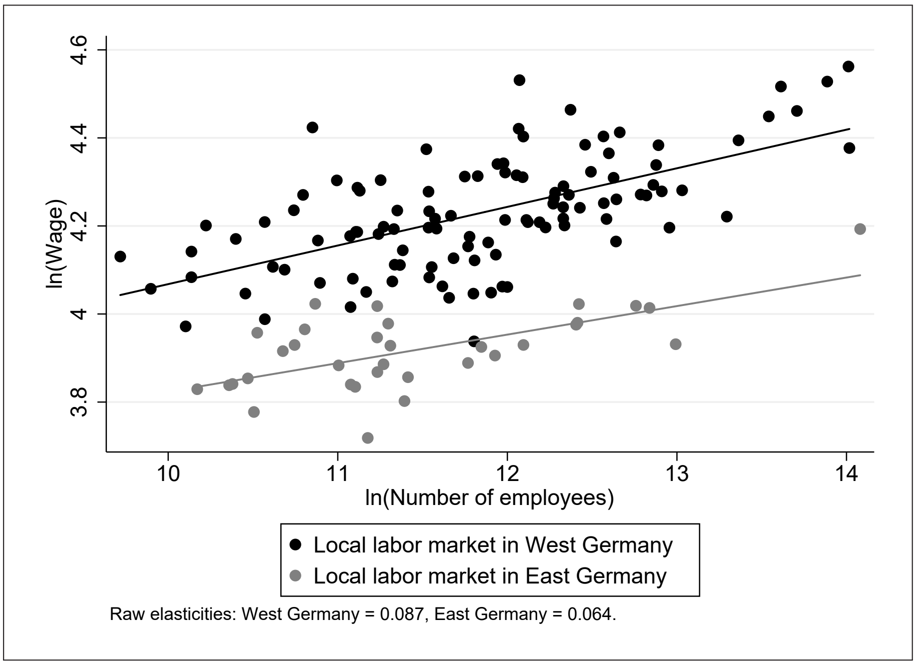
† Under the assumption that the regions are circular. ‡ Number of employees subject to social security contributions. § Share of workers with a university degree.
Note: Definition of the regions according to Kosfeld/Werner (2012). The statistics are averages for the considered period, i.e., for West Germany 1975-2011, for East Germany 1993-2011.
Sources: GENESIS-online and IAB Employment History (BeH) V09.03.00 - 130704, own calculations.

Local learning externalities should crucially depend on the amount of localized knowledge and ideas. we approximate this amount by the number of employees working in the respective labor market region similar to Bosquet/Overman (2016) and in additional specifications by the local share of high-skilled workers who are defined to have a university degree. The corresponding data is taken from the Employment History of the IAB and refers to annual regional employment on June 30th. The size of the labor market regions in terms of employment varies between 14 thousand and 1.2 million employees and the local share of high-skilled labor between 2 and 20 percent (region specific averages, see Table 1). The correlation between total regional employment and the local share of high-skilled workers is 0.38.

[16] The labor market region with the largest spatial extent is Hamburg, followed by Munich. The economic centers of these labor markets, the cities of Hamburg and Munich, are after Berlin the two largest cities in Germany in terms of local employment and population. Both have a relatively large catchment area as indicated by the large spatial extent of the labor market region.

Addressing the pronounced wage differential between East and West Germany, Figure 1 illustrates the relationship between regional employment and regional wages. It becomes obvious that wages in large local labor markets are significantly higher than wages in smaller ones. The corresponding raw elasticities are about 0.08 and the difference in the wage level between the largest and the smallest West German regional labor market (in terms of regional employment) amounts to more than 40 percent.

Figure 1: Local labor market size and regional wages



Note: The figure refers to average regional wages that are paid at the beginning of new employment relationships starting in 2011 and the size of regional labor markets in terms of number of employees subject to social security contributions.
Source: IEB V11.00.00 – 131009, own calculations.

One critical issue with regard to the chosen spatial units is that commuting patterns change over time. Therefore, the applied definition of labor market regions might be an inappropriate approximation of the shape of local labor markets decades ago. For this reason, we also repeat our estimations focusing on those workers who only acquired work experience in 1995 or later, i.e., at least five years after the reunification of East and West Germany.

3.3 The mobility of labor

The mobility of labor is an important aspect as it determines the extent to which learning externalities manifest in regional wage disparities. Considering a certain degree of learning externalities, wage disparities between small and large local labor markets arise if workers are immobile between local labor markets that differ in size since, then, individuals who work in large local labor markets accumulated in the past, ceteris paribus, on average more human capital than individuals working the same number of days in small local labor markets.

Descriptive statistics show that a worker acquires work experience in either small or large local labor markets. Mobility between labor markets that significantly differ in size is rather low. Table 2 provides information on the ratio of the size of the largest labor market and the size of the smallest labor market in which the respective worker acquired experience before one of the considered new employment relationships. In more than 60 percent of the observations the largest labor market was less than twice as large as the smallest labor market, and in less than ten percent more than ten times as large.[17]

Table 2: The ratio of the size of the largest and the smallest labor market in which a worker acquired experience

Percentile	Ratio	Percentile	Ratio
5	1.020	60	1.806
10	1.037	70	3.055
20	1.059	80	4.879
30	1.085	90	9.004
40	1.145	95	14.181
50	1.268		

Note: For each considered new employment relationship we identified the largest and the smallest labor market in which the respective worker previously acquired experience. The size of the local labor markets is measured in terms of number of employees and varies across years.
Source: IEB V11.00.00 – 131009, own calculations.

Table 3 compares the size of the labor markets in which experience was acquired and in which it is used distinguishing five categories of labor market regions according to their size. In 61 percent of all considered new employment relationships the new employer is located in a region that belongs to the same category as the average region in which experience was acquired (main diagonal), in 25 percent the current region is larger than previous ones (upper triangle) and in 14 percent smaller (lower triangle).

Table 3: The size of the labor market in which experience was acquired and in which it is used

Share in %		Size of labor market in which experience is used in thousand employees					
		≤ 125	125-250	250-500	500-1000	> 1000	Total
Average size of labor market in which a worker acquired experience in thousand employees	≤ 125	11.88	3.74	1.34	0.57	1.14	18.68
	125-250	3.07	16.91	3.92	1.37	2.09	27.35
	250-500	1.72	3.53	16.94	3.00	2.70	27.89
	500-1000	0.79	1.61	1.86	8.72	5.42	18.39
	> 1000	0.37	0.42	0.25	0.21	6.45	7.69
	Total	17.82	26.20	24.31	13.88	17.80	100.00

Note: The average size of the labor market in which a worker acquired experience denotes the size of the different labor markets in which the worker acquired experience weighted by the length of employment in the respective labor market.
Source: IEB V11.00.00 – 131009, own calculations.

Workers are not only rather immobile between local labor markets belonging to different categories as defined in Table 3, but also between labor markets that are of a comparable size. The sample mean of total work experience is 9.5 years (see Table A.2). On average, 59 percent of this previous work experience (5.7 years) refers to employment in the same labor market in which the new employer is situated. The median amounts to 79 percent. A

[17] Recall that the largest labor market is more than ten times as large as the median labor market (see Table 1).

total of 36 percent of the workers acquired all their work experience in that particular region. In contrast, 25 percent of the workers were never previously employed in the region in which the new employer is located.

Overall, a worker tends to continue to work in the labor market in which he or she acquired experience, or in a region of a comparable size. Therefore, if the individual accumulation of human capital increases with the size of the local labor market, as proposed by the learning hypothesis, it likely results in wage disparities between small rural and large urban regions.

4 Results

4.1 Baseline specification

The estimates of the pivotal parameters of Equations (4) and (2), respectively, are summarized in Table 4. Column (1) refers to ordinary least squares estimation (OLS). Since the available information on educational degrees represents only imperfect measures of skills, OLS results are likely biased. To address that workers might sort on unobserved abilities into large labor markets, we include individual fixed effects (FE, Columns (2) to (4)) as introduced by Glaeser/Maré (2001). As with De La Roca/Puga (2017), we observe that the value of experience is biased downwards if we do not control for unobserved characteristics by means of individual fixed effects (see also the results in Table B.2).[18]

The results reported in Column (1) and (2) of Table 4 refer to a restricted specification of Equation (4) assuming the depreciation rate of human capital which was acquired in the past while working to be zero. It is worth noting that in this case the within transformation which is applied to eliminate the individual fixed effect wipes out all information on experience that was acquired before the date at which the first analyzed new employment relationship of worker i started. Hence, the estimates reported in Column (1) and (2) are only based on information with regard to the size of the labor markets in which experience was acquired that refers to the period 2005 to 2011. If the depreciation of human capital is taken into account (from Column (3) in Table 4 onwards), the analysis makes use of the information on all previous employment spells of a worker.

The findings support the hypothesis that labor market size fosters the individual accumulation of human capital. Labor market size positively impacts on the value of acquired work experience which is reflected in higher future wages. According to the specification with individual fixed effects and neglecting the depreciation of human capital, the elasticity of wage with regard to the size of the labor market in which experience was acquired at one day in the past, denoted by δ, amounts to 0.116×10^{-4} (Column (2)). Based on the estimated parameters $\hat{\delta}$ and $\hat{\gamma}$ (not reported), we compute $\widehat{emp}$, the estimate of the labor market size that has to be exceeded such that the acquired work experience is rewarded with a wage premium by future employers (see Equation (2)). The results strongly suggest

[18] The results obtained for the control variables are discussed in Appendix B.1. The results of OLS estimation are virtually the same if we additionally consider those workers for whom we observe only one new employment relationship starting between 2005 and 2011. The additional results are available from the authors upon request.

that a worker accumulates valuable human capital for which he or she receives a wage premium in the future even if he or she acquires the work experience in the smallest German local labor markets with a local workforce of about 15,000 employees. The estimated critical value amounts to about 100 employees.

Table 4: Estimates of the parameters of the learning function

	(1)	(2)	(3)	(4)
$\hat{\delta}$ †	0.058***	0.116***	0.221***	0.236***
	(0.003)	(0.016)	(0.020)	(0.026)
$\widehat{emp}$	160.731***	97.489	25.588	90.735
	(52.389)	(111.521)	(22.107)	(80.945)
$\hat{\theta}$ †			3.402***	4.158***
			(0.151)	(0.281)
New employment relationships	336,286	336,286	336,286	214,319
OLS: R^2, FE: within R^2	0.613	0.183	0.197	0.261
Worker fixed effects	No	Yes	Yes	Yes

† Coefficients and standard errors multiplied by 10,000.
Note: Robust standard errors are given in parentheses which are clustered by worker. ***, ** and * indicate significance at the 1, 5 and 10 percent level. $\widehat{emp}$ calculated based on delta method and $\hat{\delta}$ and $\hat{\gamma}$ (not reported). The results in Column (1) and (2) are based on the assumption that θ is zero. The results in Column (1) to (3) are obtained using the full sample. The specification reported in Column (4) is restricted to workers who acquired work experience only 1995 or later. All specifications include control variables as well as industry, occupation, and region-year fixed effects (see Table B.1).
Source: IEB V11.00.00 – 131009, own calculations.

The results summarized in Columns (1) and (2) are based on the assumption that human capital does not depreciate over time, meaning that θ is assumed to be zero. However, this assumption is too restrictive as indicated by the results reported in Column (3). The significant differences in the parameter estimates between Column (2) and (3), as well as the notable increase in the within R^2, and the statistically highly significant estimate for θ confirm that it is important to address that a worker's human capital acquired at some point in the past has a lower value the longer time passed since acquirement. A θ of 3.402×10^{-4} means that the size of the labor market in which work experience was acquired at date $t - 365$ is weighted by factor 0.884 $(= (1 - 3.402 \times 10^{-4})^{364})$. The weight is smaller than unity suggesting that the human capital that was acquired at date $t - 365$ lost in value over the previous year. In contrast, the weight of the knowledge that was acquired at day $t - 1$ is unity.

With respect to δ, we now obtain an elasticity of 0.221×10^{-4}, and $\widehat{emp}$ is still significantly smaller than the smallest German local labor market. Both estimates are confirmed by the results reported in Column (4). The latter are based on a reduced sample restricting the analysis to individuals who acquired experience only in 1995 or later. This robustness check takes into account that the chosen definition of labor market regions might be an inappropriate approximation for the shape of local labor markets decades ago which would result in a measurement error in the pivotal explanatory variable, i.e., the size of the labor markets in which experience was acquired. However, it does not seem to be a severe problem here as the results reported in Column (3) and (4) are very similar. The reduction of the sample let the fit of the model increase. Now it explains more than one quarter of wage's within variation.

The nature of dynamic agglomeration economies in general, and learning externalities in particular, is that the benefits of working in large labor markets accumulate over time. Based on the regression results reported in Columns (3) and (4) of Table 4, Figure 2 illustrates for different levels of experience the elasticity of wage with regard to the (cumulated discounted) size of all the labor markets in which previous experience was acquired. The elasticity is increasing in the level of experience since the benefit of a one percent increase in the size of *all* labor markets in which experience was acquired is larger the higher the level of experience is.[19] Consider for example a worker with two years of work experience at date t. The corresponding elasticity is given by about 0.015, indicating that doubling the size of all labor markets in which the two years of experience were acquired results in a 1 percent higher wage at date t. For a worker with 10 years of work experience the benefit of having acquired all his or her experience in a one percent larger labor markets is larger. At this level of experience the elasticity amounts to about 0.045. Hence, doubling the size of all labor markets in which ten years of experience were acquired results in a productivity increase at date t by about three percent. At a very high level of experience the elasticity is even larger. The depreciation of accumulated human capital implies that the dynamic agglomeration gain converges towards an upper bound. If a worker has a sufficiently large amount of work experience, the size of the labor market in which the first years of experience were acquired has only a negligible impact on today's productivity and wage since, presumably, the human capital acquired at the beginning of the individual working life is (almost) fully depreciated.

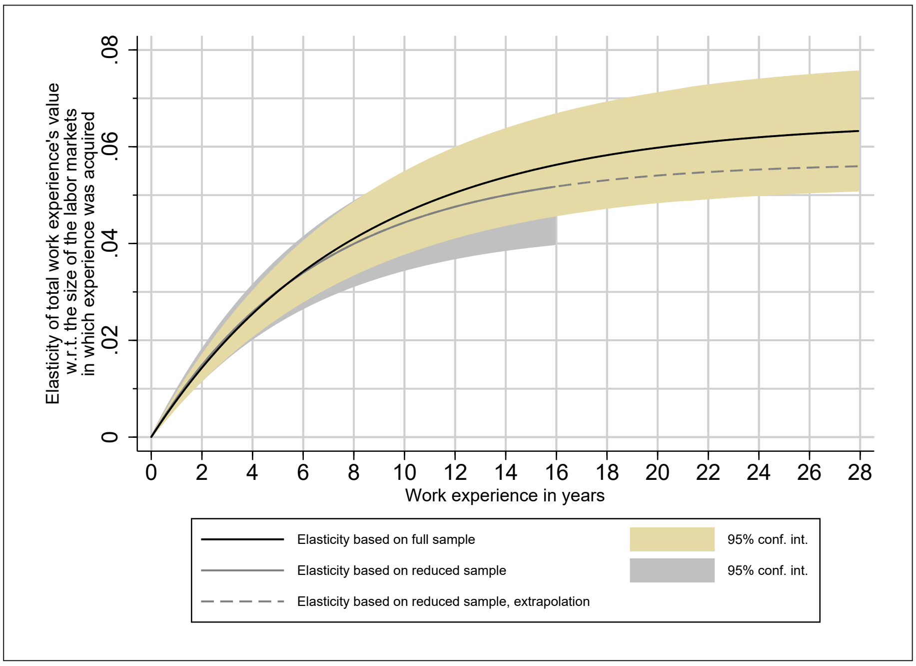
The magnitude of the elasticity shows that dynamic agglomeration economies do not only have a statistically significant effect on individual productivity growth, but its impact is also economically meaningful, especially in comparison to the magnitude of static agglomeration gains. The latter measured in terms of the elasticity of wage with regard to the employment density of the labor market in which the wage is paid is about 1.5 to 3 percent.[20] This elasticity corresponds to the magnitude of dynamic agglomerations gains at a level of experience of about 2 to 5 years. At a high level of experience the dynamic agglomeration gains are about 2 to 4 times as large as the static agglomeration benefit.[21] Since workers are rather immobile between labor markets of different size (see Table 3), the dynamic gains should explain a significant part of regional wage disparities between urban and rural labor markets. Moreover, they should be strongly related to learning externalities as we control for the number of job changes in the past which is supposed to be a proxy for dynamic matching.

[19] In general, the elasticity of the value of E days of experience with regard to the size of the labor markets in which the experience was acquired is, according to the results reported in Column (3) of Table 4, given by $0.221 \times 10^{-4} \times \sum_{k=1}^{E}(1-3.402 \times 10^{-4})^{k-1}$ (see Equation (4)).

[20] A review of recent estimates is given by Combes/Gobillon (2015). Hamann/Niebuhr/Peters (2016) obtain an estimate of about 1.5 percent using the same data set as in this paper.

[21] If we measure the size of the labor markets in which experience was acquired in terms of employment density and not in terms of total regional employment, the estimated elasticity $\hat{\delta}$ is of comparable magnitude (even a bit larger) than the estimate reported in Table 4 and amounts to 0.279×10^{-4}.

Figure 2: The magnitude of dynamic agglomeration gains



Note: The figure illustrates the regression results reported in Columns (3) and (4) of Table 4. For different levels of experience the graph denotes the percentage increase in wage, given that the local workforce would have been one percent larger in all labor markets in which previous work experience was acquired. The reduced sample contains only workers who acquired experience in 1995 or later.
Source: IEB V11.00.00 – 131009, own calculations.

4.2 The interaction of labor market size and skills

Table 5 summarizes the results of the specifications which take into account that, on the one hand, not all workers benefit equally from dynamic agglomeration gains, and that, on the other hand, large urbanized labor markets are typically characterized by an above average share of high-skilled workers who presumably are the ones from whom other workers learn the most, see Equations (5) and (6). The results in Column (1) to (3) refer to the full sample, those in Column (4) to (6) to the reduced sample which excludes workers who acquired work experience before 1995.

The specifications (1) and (4) are based on the assumption that the depreciation rate of accumulated human capital, θ, is the same for high- and non-high-skilled workers. As expected, both regressions result in a point estimate of the elasticity of wage with regard to the size of the labor markets in which experience was acquired, $\hat{\delta}_{s(i)}$, that is larger for high- than for non-high-skilled workers (subscripts hs and nhs, respectively). However, statistically the null hypothesis that both groups of workers benefit equally from acquiring experience in a larger than in a smaller labor market cannot be rejected at the five percent level (see test statistics at the bottom of the table). The threshold $\underline{\widehat{emp}}_{s(i)}$ is in both cases far below the size of the smallest local labor markets indicating that both, non-high-skilled as well as high-skilled workers, receive a wage premium even after working in those regions.[22]

[22] One control variable is the number of previous employers (see Table B.1) which is supposed to capture productivity effects which stem from an improved matching quality between workers and firms over time. We also estimated specifications with an interaction term of the worker's skill level and the number of previous employers. We find that the corresponding elasticity of wage is for high-skilled workers about three

If the assumption of equal depreciation rates is relaxed as in Columns (2) and (5), the difference between the estimated elasticities $\hat{\delta}_{\text{hs}}$ and $\hat{\delta}_{\text{nhs}}$ is larger than in the restricted case and now also statistically different from zero at the five percent level. Also the difference is economically meaningful as $\hat{\delta}_{\text{hs}}$ is about 50 percent larger than $\hat{\delta}_{\text{nhs}}$. In line with the findings of previous studies, it indicates that it is especially the productivity of high-skilled workers which increases with the size of the labor markets in which work experience was acquired suggesting that particularly those workers accumulate more human capital the larger the local labor market is in which they acquire experience.

Table 5: Estimates of the parameters of the learning function by skill level and distinguishing the impact of total regional employment and the local share of high-skilled labor

	Full sample			Reduced sample		
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\delta}_{\text{hs}}$ †	0.248***	0.286***	0.187***	0.300***	0.310***	0.140
	(0.043)	(0.034)	(0.071)	(0.056)	(0.041)	(0.089)
$\hat{\delta}_{\text{nhs}}$ †	0.210***	0.191***	0.229***	0.203***	0.200***	0.161***
	(0.020)	(0.017)	(0.028)	(0.025)	(0.023)	(0.038)
$\hat{\rho}_{\text{hs}}$ †			0.305*			0.561***
			(0.164)			(0.211)
$\hat{\rho}_{\text{nhs}}$ †			−0.119*			0.137
			(0.065)			(0.097)
$\widehat{emp}_{\text{hs}}$	20.712	13.395		91.303	85.609	
	(35.376)	(16.317)		(142.407)	(96.638)	
$\widehat{emp}_{\text{nhs}}$	19.249	15.791		57.312	56.912	
	(18.197)	(14.347)		(62.238)	(56.901)	
$\hat{\gamma}_{\text{hs}}$ †			1.136			1.952
			(1.181)			(1.485)
$\hat{\gamma}_{\text{nhs}}$ †			−1.289***			−0.016
			(0.469)			(0.649)
$\hat{\theta}$ †	3.532***			4.002***		
	(0.157)			(0.285)		
$\hat{\theta}_{\text{hs}}$ †		4.692***	4.654***		4.373***	4.457***
		(0.290)	(0.297)		(0.423)	(0.444)
$\hat{\theta}_{\text{nhs}}$ †		2.955***	2.957***		3.879***	3.904***
		(0.148)	(0.147)		(0.300)	(0.305)
New employment relationships	336,286	336,286	336,286	214,319	214,319	214,319
within R^2	0.197	0.197	0.198	0.262	0.262	0.262
F-tests (p-values):						
$H_0 : \delta_{\text{hs}} = \delta_{\text{nhs}}$	0.354	0.003	0.538	0.073	0.007	0.812
$H_0 : \theta_{\text{hs}} = \theta_{\text{nhs}}$		0.000	0.000		0.241	0.208
$H_0 : \rho_{\text{hs}} = \rho_{\text{nhs}}$			0.061			0.040

† Coefficients and standard errors multiplied by 10,000.
Note: Robust standard errors are given in parentheses which are clustered by worker. ***, ** and * indicate significance at the 1, 5 and 10 percent level. The subscript *hs* (high-skilled) refers to workers with a university degree, *nhs* (non-high-skilled) to all other workers. Columns (1), (2), (4), and (5) contain results for Equation (5), Columns (3) and (6) for Equation (6). In specification (1) and (4) it is assumed that depreciation rate θ does not vary between high- and non-high-skilled workers. The results reported in Columns (1) to (3) are obtained using the full sample, the results reported in Columns (4) to (6) using a reduced sample which does not contain new employment relationships of workers who acquired experience before 1995. All models include control variables as well as worker, industry, occupation, and region-year fixed effects (see Table B.1).
Source: IEB V11.00.00 – 131009, own calculations.

With respect to the depreciation rate $\theta_{s(i)}$, we obtain also a statistically highly significantly larger estimate in the case of the high-skilled than in the case of the non-high-skilled workers. It suggests that the human capital which was acquired by high-skilled workers while working depreciates faster than the human capital acquired by non-high-skilled workers.

times as large as for non-high-skilled workers (about 0.075 [s.e.: 0.005] vs. 0.025 [0.002]). However, taking this heterogeneity into account has virtually no effect on the estimates reported in Table 5. The additional regression results are available from the authors upon request.

One explanation might be that especially in the segment of high-skilled labor the skills demanded faster change due to technological progress. With regard to the wage premium workers receive for their work experience, it means that high-skilled workers do not benefit that long from having acquired experience in a large labor market at some point in the past as do non-high-skilled workers. For example, the wage premium that a high-skilled worker receives at day t for the experience he or she acquired 10 years earlier is 18 percent $(= (1-4.692 \times 10^{-4})^{3652.5})$ of the wage premium he or she received initially for that unit of experience. In the case of a non-high-skilled worker about one third of the initial wage premium is left.

In Column (3) and (6) of Table 5 we report results for Equation (6) in order to analyze the role of the share of high-skilled labor in the local labor markets in which experience was acquired. In contrast to all previous specifications, elasticity $\delta_{s(i)}$ now measures the effect of labor market size on the value of acquired experience as reflected in future wages *conditional* on the local share of high-skilled labor. The effect of the latter is measured by $\rho_{s(i)}$. For non-high-skilled workers, we do not find that the wage premium which they receive for their work experience is ceteris paribus statistically significantly larger the higher the share of high-skilled labor in the labor markets were in which they acquired work experience. In Column (3) the point estimate of ρ_{nhs} is even negative. The estimates of δ_{nhs} change only slightly compared to the results reported in Column (2) and (5), respectively. Hence, we do not find evidence that the dynamic agglomeration gains experienced by non-high-skilled labor are related to the skill structure of urban labor markets which are typically characterized by an above average share of high-skilled labor. This result surprises presuming that the high-skilled workers are the ones from whom other workers learn the most. Already List (1838) noted that the interaction of higher and lower skilled workers may lead to imitations by the latter (see also Jovanovic/Rob, 1989).

Turning to the high-skilled workers, they, in contrast to the non-high-skilled workers, benefit (additionally) from external effects that are related to the local share of high-skilled labor. One explanation is that new ideas and knowledge presumably are especially generated if high-skilled workers meet among each other (Jovanovic/Rob, 1989). Accordingly, high-skilled workers receive ceteris paribus a larger wage premium the higher the share of high-skilled labor in the local labor markets was in which work experience was acquired. In Column (6) this effect is statistically highly significant at the one percent level, in Column (3) at least at the 10 percent level. The magnitude of the effect remains somewhat ambiguous. Based on the reduced sample the estimated elasticity is almost twice as large as based on the full sample. However, in both cases it is larger than the respective estimate of δ_{hs} and economically meaningful. Moreover, both regression results suggest that the difference in the skill composition of the local workforce between urban and non-urban labor markets explains as to why high-skilled workers benefit more from acquiring work experience in a large urban labor market with regard to future productivity than do non-high-skilled workers as reported in Column (2) and (5). Once controlling for the labor markets' skill-composition, the null hypothesis that the elasticities δ_{hs} and δ_{nhs} equal each other cannot be rejected at conventional levels any longer.[23]

[23] According to the results reported in Column (6) the null hypothesis that δ_{hs} is zero cannot be rejected at

Considering both, labor market size as well as the local share of high-skilled labor, simultaneously in the analysis, it is not possible to compute estimates for the thresholds $\underline{emp}$ and $\underline{hskill/emp}$ explicitly. A linear combination $\hat{\gamma}_{s(i)}$ is reported instead (compare Equation (6)). It at least enables testing whether $-\hat{\delta}_{s(i)}\ln(emp_{r,t}) - \hat{\rho}_{s(i)}\ln(hskill_{r,t}/emp_{r,t})$ is significantly smaller than $\hat{\gamma}_{s(i)}$. This condition is fulfilled for each considered region-year-combination.

5 Conclusions

This paper provides empirical evidence as to why wages are higher in large, rather urban than in small, rather rural local labor markets. The focus lies on learning externalities which are discussed to be one mechanism behind dynamic agglomeration economies. Using administrative data for Germany, we analyze more than 300,000 wages associated with new employment relationships starting between 2005 and 2011. These wages contain important information as to how firms value work experience when they hire a new worker. Previous studies showed that an additional wage premium is paid if experience was acquired in one of the very largest cities of a country.

Using information on the individual employment biographies from 1975 onwards, we extend this literature by estimating the elasticity of wage with regard to the size of the local labor markets in terms of employment in which experience was acquired. The empirical setup takes into account that agglomeration gains based on learning externalities are supposed to cumulate and depreciate over time just like the acquired human capital. Furthermore, we analyze whether local employment has to exceed a certain threshold so that the acquired work experience is rewarded with a wage premium by future employers and whether the identified dynamic agglomeration gains are related to the special composition of the local workforce in agglomerated labor markets with respect to skills. The identified effects should be strongly related to learning externalities. We control for observable as well as unobservable characteristics of the worker and the region in which the new employer is located, as well as for characteristics of the firm and the local industry. We also take into account other channels of agglomeration economies, inter alia, dynamic matching. Furthermore, our results are also in line with previous findings that the value of experience is predominately determined by the size of the labor market in which experience was acquired rather than by the labor market in which it is used.

In accordance with the idea that dynamic agglomeration gains cumulate over time, the estimated elasticity of wage with regard to the (cumulated) size of the labor markets in which experience was acquired increases with the level of experience. However, the identified dynamic agglomeration gain converges towards an upper bound over working lifetime. If a worker has a sufficiently large amount of work experience, the size of the labor market in

conventional levels. In addition to the fact that the point estimate decreases by one half if the share of high-skilled labor is considered in the model (compare Columns (5) and (6)), one explanation for the insignificant coefficient is that the standard error of $\delta_{s(i)}$ increases at the same time. Hence, the (remaining) effect of total labor market size is less precisely estimated, likely due to the correlation between labor market size and the local share of high-skilled labor. Therefore, it is worth noting that $\hat{\delta}_{\text{hs}}$ in Column (6) is only slightly smaller than the corresponding statistically highly significant estimate in Column (3) and also only slightly smaller than the statistically highly significant estimate of δ_{nhs} in Column (5).

which the first years of experience were acquired has only a negligible (direct) impact on today's productivity and wages likely because the human capital acquired in the first years of the individual career is at some point (almost) fully depreciated.[24]

After two years of working, the estimated elasticity of wage with regard to the size of the labor markets in which experience was acquired amounts to more than 0.015, after ten years to more than 0.045 and after 20 and more to more than 0.06. The latter elasticity, for example, implies that today's productivity of a worker with 20 years of experience would be about four to five percent higher if the worker would have gained his or her experience in local labor markets double the size of the labor markets in which he or she actually was working. At such a high level of experience the dynamic agglomeration gain is about 2 to 4 times as large as static agglomeration gains recently estimated by other studies. Furthermore, our results indicate that the magnitude of dynamic agglomeration gains is some what larger than suggested by the results of De La Roca/Puga (2017) as well as Carlsen/Rattsø/Stokke (2016).[25] One explanation might be that it is not possible to distinguish the dynamic agglomeration gain and the evolution of the static effect applying the two step estimation strategy as these authors did (see discussion by Combes/Gobillon, 2015), an other that they distinguish only three classes of cities in which experience was acquired.

A further result of our analysis is that valuable human capital is acquired even by working in those (rural) labor markets with the smallest local workforce, meaning that virtually no threshold exists which the labor market size has to exceed so that work experience is rewarded with a wage premium by future employers. Taking into account that especially high-skilled workers benefit from acquiring experience in large urban labor markets as also shown by previous studies, our results suggest, that high-skilled workers gain more since they additionally benefit from the typical high share of high-skilled labor in large urban labor markets. One explanation is that new ideas and knowledge are presumably especially generated if high-skilled workers come together (Jovanovic/Rob, 1989). Once controlling for the workforce composition in the local labor markets in which experience was acquired with respect to the skill level, we do not find any longer that high-skilled workers benefit more from acquiring experience in a large labor market than do non-high-skilled workers. For non-high-skilled workers, we, in contrast, do not find evidence that the dynamic agglomeration gains they experience are related to the typically above-average share of high-skilled labor in large urbanized labor markets. This result surprises presuming that the high-skilled workers are the ones from whom others learn the most. In 1838 Friedrich List had already noted that the interaction of skilled and unskilled workers may lead to imitations by the latter (see also Jovanovic/Rob, 1989). However, an explanation might be that learning takes predominately place within groups of workers whose members have a comparable educational level.

[24] Nevertheless, there still might exists an indirect effect as the location in which the first years of work experience were acquired likely affects the locations in which experience was acquired in the subsequent years due to the rather low spatial mobility of individuals over working life as discussed by Bosquet/Overman (2016).

[25] Their results suggests that the corresponding elasticity of wage with regard to the size of the labor markets in which experience was acquired amounts at a level of about 8 years of local work experience to, respectively, 0.029 and 0.015 (difference between the reported medium-term and initial/static earnings premium). According to our results the elasticity is at this level of experience is about 0.04.

With regard to the development of rural areas our results casts doubts on political measures which aim at preventing especially graduates and young workers with good labor market expectations to migrate to larger urban labor markets. If the identified dynamic agglomeration gains stem from learning externalities, such measures result in a slower individual human capital accumulation by these individuals. In order to promote the individual human capital accumulation, it could be better to support workers in acquiring experience outside the (rural) local labor market, but at the same time to create attractive conditions for subsequent return migration. For example, local firms could employ those young people who leave rural areas to go to a university as working students where the students work during semester break and after completing studies. Similarly, the interregional cooperation of firms with regard to vocational training programs may create opportunities for apprentices to learn something about the technologies used by other firms. Furthermore, the results indicate that further training is especially important for workers in small (rural) local labor markets.

A further interesting question for future research is whether dynamic agglomeration economies are increasing in labor market size without bound, or whether the benefit decreases beyond some upper threshold since, inter alia, urban congestion may hinder the transmission of skills as discussed by, for example, Duranton/Puga (2004). In the case of Germany this is likely not the case since even the largest local labor markets with the cities of Berlin, Hamburg, Munich, and Frankfurt as their economic centers are compared to so-called megacities rather small.

Appendix

A Further information on data

The units of observation in our analysis are new employment relationships within the period between 2005 and 2011. We restrict the analysis to new employment of individuals to whom information on the entire employment biography is available. As the IEB contains information on employment in West Germany only from 1975 onwards, we exclude all workers who were born before 1960. Reliable and complete information on employment in East Germany is only available from 1993 onwards. Therefore, we also exclude all workers who presumably worked in East Germany before reunification, i.e., all workers for whom we do not observe a spell of employment before 1990 and who were born before 1977. Additionally, we do not consider individuals who worked before 1993 in a labor market region which today contains parts of former East and West Germany. Furthermore, we restrict the analysis to workers of German nationality. Since information on the place of birth is not available, it is the only possibility to exclude immigrants. This is necessary as for this group of individuals, information on the entire previous work experience is not available.

In our analysis, we only consider new spells of employment with a length of at least seven days that refer to full-time employment subject to social security contributions outside the public sector and outside of the temporary employment industry. We do not consider apprenticeships, nor new employment relationships that start simultaneously with another employment relationship or with a measure of active labor market policy. In the latter case we cannot ensure that this employment is not publicly subsidized. Furthermore, new employment relationships with wages less than double the limit for marginal employment as well as recalls, i.e., cases in which a worker starts to work in an establishment in which he or she worked at least once during the previous 28 days, are not considered. If a worker is already employed at the starting date of the new employment relationship by another establishment, we consider the new employment relationship only if the previous spell of employment ends within 7 days. Furthermore, we exclude a new employment relationship if it is the first spell of employment in a person's life.

The dependent variable in our analysis is the wage of a new employment relationship. The first employment spell in the IEB of a new employment relationship ends, at the latest, by December 31 of the year in which the new employment relationship starts. By dividing total reported earnings by the length of the spell, daily wages are obtained which we use as the dependent variable. Information on actual working days or contract hours is not available. Firms report earnings only up to the upper limit for social security contributions. Therefore, the wage information in the IEB is right censored. We follow Reichelt (2015) and apply an interval regression, a generalization of tobit regression, to predict the wages above the threshold (about 6% of the observations). See Reichelt (2015) for a detailed description on how interval regression is applied to impute right-censored wages. For the imputation we use information on sex, age, nationality, educational level, industry and the region in which the establishment is located. The results of our regression analysis do not change when we use the reported wages as dependent variable instead of the imputed wages. Table A.1

provides information on the definition of all variables used in this analysis and Table A.2 summary statistics.

Table A.1: Variables - definitions and sources

Variable	Definition	Source
Gross daily wage	Daily wages are calculated by dividing the reported total earning from employment spell by the length of the spell. Wages above the upper limit for social security contributions are imputed.	IEB
Size of local labor market in which experience was acquired	Size of regional labor market regions, defined according to Kosfeld/Werner (2012), in which work experience was acquired until the considered new employment relationship. Measured in terms of employment subject to social security contributions. The share of high-skilled labor refers to workers with an university degree.	IEB
Work experience	Length of previous employment spells measured on a daily basis. Marginal employment is not considered, nor are employment spells that refer to measures of active labor market policies. We also compute the work experience that was acquired in the largest German labor market regions, i.e., Berlin, Hamburg, and Munich for the analysis described in Appendix B.2.	IEB
Tenure	The length of an employment spell in months that refers to a new employment relationship. The spell ends at the latest by December 31 of the year in which the new employment relationship starts.	IEB
ln(Number of employers)	The number of unique establishment identifiers until the considered new employment relationship, by person.	IEB
Educational level of the worker	A categorical variable that combines information on the highest schooling level attained, completed vocational training, and university degree. For some spells of employment this information is missing. If so, we use the information from previous employment spells following Fitzenberger/Osikominu/Völter (2005).	IEB
Gender	Dummy variable distinguishing male and female workers.	IEB
Length of non-employment	The number of days between the beginning of the new employment relationship and the end of the previous employment spell.	IEB
Pre-employment status	Dummy variables referring to the 28 days before the considered transition to employment - unemployment benefits (Arbeitslosengeld I) - unemployment assistance (Arbeitslosengeld II / Arbeitslosenhilfe) - unemployed and registered as a job seeker - not unemployed, but registered as a job seeker - participating in active labor market policy programms.	IEB

Table A.1 continued

Variable	Definition	Source
Firm characteristics	Number of employees, share of workers with a university degree, share of workers with no completed vocational training/no university degree, share of workers younger than 30 years old, share of workers 50 years old or older. The information refers to the last reference date (June 30) before the considered transition.	Establishment History Panel (BHP)
Industry share	Logarithm of the employment share of the industry (2-digit level: 88 industries) in total regional employment.*	Employment statistics of the Federal Employment Agency (FEA)
Industrial diversity	Logarithm of the inverse Herfindahl index based on the employment shares of the different industries in total regional employment. The own industry is excluded when the inverse Herfindahl index is calculated.*	FEA
Human capital within the local industry	Share of workers with a university degree in total employment and share of workers without completed vocational training/university degree in the same industry and regional labor market.*	FEA
Skill-specific unemployment rate of the regional labor market	The share of persons registered as unemployed in the number of persons who are registered as unemployed or employed in the region. We distinguish three groups: persons with a university degree, persons with a completed vocational training, and persons without completed vocational training/university degree.*	(Un-)employment statistics of the Federal Employment Agency
Industry fixed effects	Fixed effects for 88 distinct industries (2-digit level according to the classification from 2008). In 2008, there was a change in the industry classification. If an establishment is observed before and after 2008, we assign the spells of employment from 2005–2007 to the industry that the firm reports in 2008 (or later). If an establishment identifier shows up only for 2005–2007, we use a correlation matrix between the old and new industry classification as described by Eberle et al. (2011).	IEB
Occupation fixed effects	Fixed effects for 335 distinct occupations.	IEB
Region-year fixed effects	Time varying fixed effects for the location of the establishment in which a person starts to work. The location refers to one of 141 functional labor markets which are defined according to commuting intensity between NUTS-3-regions (see Kosfeld/Werner, 2012).	IEB

* The information refers to June 30th of the previous year.
Source: own description.

Table A.2: Summary statistics

	mean	sd	min	max
ln(imputed gross daily wage)	4.102	0.455	3.267	7.192
Total work experience in days	3475.382	2644.871	1.000	13220.000
Experience acquired in Berlin / Hamburg / Munich in days	380.287	1199.576	0.000	13023.000
Size of local labor market in which experience was acquired§				
ln(Number of employees)	12.493	0.841	9.512	14.187
Share of high-skilled employment	0.099	0.039	0.013	0.325
Tenure in month	5.784	3.540	0.033	12.000
ln(Number of previous employers)†	1.325	0.758	0.000	4.331
Length of non-employment				
0-28 days (job-to-job transition)	0.561	0.496	0.000	1.000
29-92 days	0.161	0.368	0.000	1.000
93 days - 1 year	0.169	0.375	0.000	1.000
$>$ 1 year	0.108	0.311	0.000	1.000
Pre-employment status				
Not registered as job seeker	0.552	0.497	0.000	1.000
Unemployed and registered as a job seeker	0.339	0.473	0.000	1.000
Not unemployed, but registered as a job seeker	0.109	0.312	0.000	1.000
Participation in measures of active labor market policy	0.061	0.240	0.000	1.000
Public assistance benefits				
No benefits	0.664	0.472	0.000	1.000
Unemployment benefit (ALG I)	0.235	0.443	0.000	1.000
Unemployment assistance (ALG II, ALHI)	0.068	0.252	0.000	1.000
Education:				
Secondary/intermediate school leaving certificate				
... without completed vocational training	0.071	0.257	0.000	1.000
... with completed vocational training	0.697	0.459	0.000	1.000
Upper secondary school leaving certificate				
... without completed vocational training	0.015	0.123	0.000	1.000
... with completed vocational training	0.099	0.299	0.000	1.000
Completion of a university of applied sciences	0.045	0.208	0.000	1.000
College/ university degree	0.072	0.258	0.000	1.000
Female worker	0.329	0.470	0.000	1.000
ln(Number of workers within the establishment)	3.830	1.883	0.000	*
Share high-skilled workers in establishment	0.103	0.193	0.000	1.000
Share low-skilled workers in establishment	0.155	0.209	0.000	1.000
Share of middle aged workers in establishment	0.522	0.179	-0.000	1.000
Share of older workers in establishment	0.202	0.151	0.000	1.000
ln(Employment share of the industry within the region)	-3.528	1.045	-12.732	-0.855
ln((Herfindahl index based on local industry shares)$^{-1}$)	3.027	0.266	1.444	3.551
Share high-skilled workers in local industry	0.099	0.104	0.000	0.855
Share low-skilled workers in local industry	0.193	0.089	0.000	1.000
ln(Local unemployment rate among high-skilled labor)‡	1.855	0.419	0.294	2.838
ln(Local unemployment rate among skilled labor)‡	2.259	0.433	0.981	3.484
ln(Local unemployment rate among low-skilled labor)‡	3.402	0.375	2.245	4.293
Observations	336,286			

§ Weighted average size of the labor markets in which an individual worker acquired experience before the considered new employment relationship starts, computed on individual level and weighted by the respective length of the previous spell of employment. † For less than 1 percent of the observations the number of previous employers exceeds 18, for less than 10 percent 9 previous employers. ‡ In the empirical analysis this variable is set to zero if the considered worker belongs to another skill level. Therefore, the summary statistics refer only to transitions of, respectively, high-, medium- and low-skilled workers. * Due to data protection guidelines not reported. For less than 1 percent of the observations firm size exceeds about 7500 employees.
Source: IEB V11.00.00 – 131009, own calculations.

B Further results

B.1 Control variables

Table B.1 summarizes the regression results for the control variables that we use in our analysis. The results refer to Equation (4) with θ being zero, compare Column (1) and (2) of Table 4. Column (1) in Table B.1 shows the results of ordinary least squares estimation (OLS) and Column (2) of the preferred estimation with individual fixed effects (FE) taking into account that workers might sort on unobserved abilities into large labor markets. The comparison of OLS and FE results shows that the OLS estimates are in most cases biased upwards. However, the sign of the estimated coefficients is in both models almost always the same and as expected. The greater the highest educational degree of a worker, the larger is the wage at the beginning of the considered new employment relationship. For example, workers with a university degree receive a 26 percent ($e^{0.233}-1$) higher wage than workers with a secondary/intermediate school completion certificate and completed vocational training.

Since the wage rate that we use as a dependent variable refers to the average wage rate that is paid until December 31 of the year in which the employment relationship starts (see Appendix A), we include the length of the considered spell of employment, measured in months. It confirms that tenure affects the wage rate positively, the monthly increase amounts to 0.8 percent.

As results by Yankow (2006) suggest, dynamic agglomeration economies are based not only on learning effects, but also on a higher quantity of matches between workers and firms. Therefore, we include the number of previous employers as control variable, meaning the number of different establishments a worker was working in until the considered new spell of employment starts. If mobility between establishments enhances the quality of matches, the number of previous employers has a positive impact on wages. The empirical results confirm this hypothesis. We do find the expected positive impact when controlling for unobserved individual characteristics. The corresponding elasticity amounts to about 0.06.

With respect to the pre-employment status of a worker, the results show that the longer the period of non-employment before the considered new spell of employment, the lower the corresponding wage. Non-employment of more than one year results in a wage loss of about four percent. Following Mincer/Ofek (1982), a reasonable explanation is that non-employment accelerates the depreciation of human capital. Since we assume that work experience depreciates at a constant rate irrespective of a worker's employment status (compare Equation (1)), it is worth noting that Mincer/Ofek (1982) also provide evidence that non-employment has only a temporary negative effect on individual's human capital, meaning that eroded human capital is restored after an individual returns to work.

In addition, the estimation results indicate that a worker receives a 2.5 percent lower wage if he or she was registered by the Federal Employment Agency as a job seeker before the considered transition to employment than if he or she was not. This indicates a selection effect. If workers have good labor market expectations, they seldom register as a job seeker.

Table B.1: Results for control variables

Dependent variable: logarithmic wages in new employment relationships	OLS (1)		FE (2)	
Education:				
Secondary / intermediate school leaving certificate				
...without completed vocational training	-0.132^{***}	(0.020)	-0.023	(0.027)
...with completed vocational training		*Reference*		
Upper secondary school leaving certificate				
...without completed vocational training	-0.012	(0.021)	-0.084^{***}	(0.029)
...with completed vocational training	0.094^{***}	(0.003)	0.012^{**}	(0.005)
Completion of a university of applied sciences	0.261^{***}	(0.013)	0.167^{***}	(0.016)
College / university degree	0.404^{***}	(0.013)	0.233^{***}	(0.016)
Female worker	-0.154^{***}	(0.002)		
Tenure	0.011^{***}	(0.000)	0.008^{***}	(0.002)
ln(Number of previous employers)	-0.015^{***}	(0.001)	0.058^{***}	(0.002)
Length of non-employment				
0-28 days (job-to-job transition)		*Reference*		
28-92 days	-0.051^{***}	(0.002)	-0.030^{***}	(0.002)
93 days - 1 year	-0.068^{***}	(0.002)	-0.034^{***}	(0.002)
$>$ 1 year	-0.079^{***}	(0.002)	-0.043^{***}	(0.002)
Pre-employment status				
Not registered as job seeker		*Reference*		
Unemployed and registered as a job seeker	-0.064^{***}	(0.002)	-0.025^{***}	(0.002)
Not unemployed, but registered as a job seeker	-0.071^{***}	(0.001)	-0.026^{***}	(0.002)
Participation in measures of active labor market policy	-0.026^{***}	(0.002)	-0.012^{***}	(0.002)
Public assistance benefits				
No benefit		*Reference*		
Unemployment benefit (ALG I)	0.012^{***}	(0.002)	0.008^{***}	(0.002)
Unemployment assistance (ALG II, ALHI)	-0.033^{***}	(0.002)	-0.001	(0.002)
ln(Number of workers within the establishment)	0.032^{***}	(0.000)	0.017^{***}	(0.000)
Share of high-skilled workers in establishment	0.170^{***}	(0.005)	0.057^{***}	(0.004)
Share of low-skilled workers in establishment	-0.054^{***}	(0.003)	-0.025^{***}	(0.003)
Share of middle aged workers in establishment	0.131^{***}	(0.004)	0.076^{***}	(0.003)
Share of older workers in establishment	0.103^{***}	(0.004)	0.072^{***}	(0.004)
ln(Employment share of the industry within the region)	0.006^{***}	(0.001)	0.001	(0.001)
ln((Herfindahl index based on local industry shares)$^{-1}$)	0.007	(0.011)	-0.020	(0.014)
Share of high-skilled workers in local industry	0.170^{***}	(0.013)	0.086^{***}	(0.012)
Share of low-skilled workers in local industry	-0.019^{***}	(0.011)	-0.008	(0.011)
ln(Local unemployment rate among high-skilled labor)	-0.013^{*}	(0.009)	-0.083^{***}	(0.010)
ln(Local unemployment rate among skilled labor)	0.004	(0.008)	-0.023^{**}	(0.009)
ln(Local unemployment rate among low-skilled labor)	0.029^{***}	(0.010)	-0.013	(0.012)
Constant	3.683^{***}	(0.045)	3.684^{***}	(0.052)
Observations	336,286		336,286	
OLS: R^2, FE: within R^2	0.613		0.183	
Worker fixed effects	No		Yes	

Note: Robust standard errors are given in parentheses which are clustered by worker. ***, ** and * indicate significance at the 1, 5 and 10 percent level. The results refer Equation (4) with θ being zero, compare Column (1) and (2) of Table 4. The models include industry, occupation, and region-year fixed effects as well as total work experience and the pivotal variable $\sum_{\tau=1}^{t-1} I(O_{i,\tau}=1) \times emp_{r(i,\tau),\tau}$.
Source: IEB V11.00.00 – 131009, own calculations.

A similar explanation likely holds for the negative effect of participation in measures of active labor market policies. Furthermore, workers who received unemployment benefit (ALG I) before the considered transition to employment have a 0.8 percent higher productivity as reflected in wage than workers who received no public assistant benefit or unemployment assistance. Again, this likely is related to proximity to the labor market. Unemployment benefits in Germany are only paid within the first year after the end of an employment spell of at least one year (with exceptions). Thereafter, either no public assistant benefit or unemployment assistance is paid, depending on the wealth of the household.

In order to address heterogeneity in firm productivity, we include establishment size and information on the firm's workforce composition with respect to the skill level and the age of the workers. Furthermore, time-invariant heterogeneity across firms belonging to different industries is captured by industry fixed effects. The results confirm that large firms and firms with a more skilled labor workforce are more productive than others and pay higher wages. Doubling an establishment workforce comes along with an about one percent higher productivity and a ten percentage point increase in the share of high-skilled workers with a 0.6 percent higher productivity. The age structure of a firm's workforce is correlated with individual productivity as well. A shift from younger towards middle aged or older workers comes along with higher wages. A reasonable explanation for this is complementarities between differently aged workers. More than 50 percent of the analyzed wages refer to young workers. Therefore, the positive coefficients may be explained by a high productivity of young workers if their share is low. This interpretation is in line with results obtained by, e.g., Garloff/Roth (2016). They show that productivity of young workers is higher, the lower their share is in the local workforce.[a]

The agglomeration economies literature points out that the local industry structure also determines productivity. As for example formally shown by Duranton/Puga (2004), localization economies generate advantages to urban specialization if agglomeration causes congestion costs. Therefore, we control for localization economies by using the local industry share. To address that industrial diversity might also be beneficial due to urbanization externalities as suggested by Jacobs (1969) and formally shown by Duranton/Puga (2001), we follow Combes/Magnac/Robin (2004) and consider the inverse of a Herfindahl index based on the industry shares within local employment. If all industries have an equal share in the local industry, the inverse of a Herfindahl index corresponds to the number of locally operating industries. When industries have unequal shares, it indicates the 'equivalent' number of industries, i.e., the number of industries that would result in the same degree of industrial concentration, given equal industry shares.[b] The results of the fixed effect model suggest that neither the share of the own industry nor the diversity of the industry structure in the local labor market affects individual productivity.

Not only the agglomeration economics literature, but also another strand focuses on the

[a] We also estimate specifications without firm variables as they might cause a simultaneity bias in the estimations (see discussion by Combes/Gobillon, 2015). The results with regard to our pivotal explanatory variables change only marginally. The results are available upon request.

[b] As suggested by Combes/Gobillon (2015), we remove the own industry from the computation of the index which eases interpretation since the share of the own industry within the local economy already measures local specialization.

impact of the amount of localized human capital on wages referring to human capital externalities (see, e.g., Moretti, 2004a; Ciccone/Peri, 2006). Parts of these effects are captured by the region-fixed effects included in the model. In addition, we also consider the industry-specific regional share of high and low-skilled labor in our analysis. The empirical results point to a positive effect of the local industry-specific share of high-skilled labor. A ten percentage-points increase in this share is associated with a 0.9 percent higher productivity. However, for the interpretation of this contemporaneous effect it is important to note that only the composite of an externality effect and a substitution effect is identified. To identify learning benefits, which also might depend on human capital externalities, this paper does not focus on the analysis of contemporaneous effects, but on benefits of having *previously* worked in an urbanized labor market with a large number of workers and a high share of high-skilled labor.

Finally, we control for skill-specific unemployment rates to address that the literature on the wage curve provides robust empirical evidence of a negative relationship between wages and unemployment (e.g., Blanchflower/Oswald, 1990). We do obtain negative elasticities, although the coefficient of the regional unemployment rate among low skilled labor is not statistically different from zero.

B.2 Adopting the empirical strategy applied by De La Roca/Puga

Table B.2 summarizes results that we obtain adopting the empirical strategy first applied by De La Roca/Puga (2017) to analyze dynamic agglomeration gains. It focuses on the wage premium that a worker receives if he or she acquired work experience in one of the very largest cities of a country. Accordingly, we estimate a special case of Equation (1) where we impose restrictions on $v_{r,\tau}$ such that the number of parameters reduces. In this case, Equation (1) simplifies to Equation (B.1) with $E_{i,s,t}$ denoting the amount of experience that was acquired until $t-1$ in city s and N the number of distinguished classes of cities, compare De La Roca/Puga (2017: eq. 1).[c] Using Spanish data, De La Roca/Puga distinguish experience according to few classes of cities in which it was acquired: in Madrid/Barcelona, Valencia/Sevilla/Zaragoza, or elsewhere in Spain. Similarly, we focus on the benefit of acquiring experience in Germany's largest local labor markets: Berlin, Hamburg, and Munich.[d] Again following De La Roca/Puga, we also include the amount of overall experience in the analysis so that the estimated effect of experience acquired in Berlin, Hamburg, or Munich refers to the difference in the value of experience acquired there and experience acquired elsewhere in Germany.

[c] In contrast to Equation (1) the value of work experience is in Equation (B.1) allowed to vary depending on the location in which the experience is used. We refrain from that in the main part of this paper (see also Appendix B.3). De La Roca/Puga also estimate further specifications, e.g., taking into account that workers with high (unobserved) abilities benefit more from acquiring experience in large cities. We focus here on the replication of their baseline specification based on German data.

[d] The local labor market regions of Berlin, Hamburg, and Munich are considered as one group. We also estimated a specification where we distinguish experience acquired in the three labor markets. When controlling for unobservable abilities of the workers by means of individual fixed effects, we found no significant differences between the value of experience acquired in the three largest German cities.

$$w_{i,t} = u_i + \mu_{r(i,t),y(t)} + \sum_{s=1}^{N} \nu_{s,r(i,t)} E_{i,s,t} + \mathbf{x}'_{i,t}\beta + \varepsilon_{i,t} \tag{B.1}$$

The estimation approach described by Equation (B.1) enables a comparison of the marginal value of experience acquired in different groups of cities to assess the magnitude of dynamic agglomeration benefits. However, to obtain general results with regard to the impact of labor market size on dynamic gains is difficult. The two-step procedure suggested by Combes/Gobillon (2015) requires in the first step not only few parameters $\nu_{s,\tau}$ to be estimated, but many. De La Roca/Puga (2017) assess the magnitude of dynamic agglomeration economies by comparing the elasticity of static agglomeration gains measured by time invariant city fixed effects μ_r (compare Equation (B.1)) with regard to labor market density to the 'medium term agglomeration gain' which they measure as the elasticity of the city fixed effects plus 7.7 years$\times\nu_{r,r}$ with regard to labor market density (7.7 years is the sample mean of local experience). They find that this medium term agglomeration gain is more than twice as large as the static agglomeration gain. However, the dynamic agglomerations gain (the difference between the medium term and the static wage premium) is identified distinguishing only three classes of cities in which experience was acquired.

Table B.2 summarizes the results obtained when estimating Equation (B.1) based on German data. As expected, we find that one year of experience acquired in the largest German local labor markets has a significantly higher value than experience acquired in the rest of the country. The inclusion of individual fixed effects in specification (2) let the value of experience increase, indicating a negative correlation of unobserved abilities and work experience.[e] The magnitude of the agglomeration benefit is discussed below. In order to test whether the value of experience depends on where it is used, we consider similar to De La Roca/Puga interaction effects between the experience variables and an indicator for moving to the respective other group of labor markets. The corresponding results of the fixed effects model in Column (2) suggest that the value of experience acquired in the largest labor markets does not change when transferring it to smaller labor markets. The value of experience acquired outside the large labor markets increases slightly if it is used in Berlin, Hamburg, or Munich.

Following De La Roca/Puga, specification (3) additionally contains the square of experience to let the marginal value of experience decay with more experience. Furthermore, interaction effects of experience acquired in the largest labor markets and overall experience are included. They allow for heterogeneous effects for less and more experienced workers (De La Roca/Puga, 2017). Qualitatively, we obtain the same results as De La Roca/Puga: (i) Experience acquired in the largest local labor markets has a significantly higher value than experience acquired elsewhere. (ii) The marginal gain of working in one of the largest labor markets is higher for individuals with less work experience than for more experienced workers. This is particularly true for workers who previously worked elsewhere in the country. (iii) The value of experience acquired in the largest labor markets is highly portable to smaller labor markets which strongly supports the hypothesis that learning externalities play an important role. (iv) Experience acquired in the rest of the country has a higher

[e] This effect also shows up in the results reported by De La Roca/Puga (2017: Table 1).

value if it is used in the largest local labor markets than in the rest of the country. However, the location in which experience was acquired has a stronger impact on its value than the location where it is used. The first year of experience acquired in Berlin, Hamburg or Munich increases wages by about 1.3 percent ($e^{0.01338-0.00047}-1$) relative to having worked elsewhere and independently of the new job location. In comparison, the value of the first year of experience acquired outside the largest local labor markets increases by less than 0.7 percent if the worker moves to Berlin, Hamburg or Munich. Qualitatively, the results are the same as obtained by De La Roca/Puga (2017) for Spain. Quantitatively, the identified agglomeration benefit for the largest German agglomerations is somewhat smaller than the dynamic agglomeration gains obtained by De La Roca/Puga (2017) for Madrid and Barcelona and by Matano/Naticchioni (2016) for Rome and Milan. Their results indicate that the value of the first year work experience acquired in the largest cities of the considered country has, respectively, a three percent and two percent higher value than the first year acquired elsewhere.[f]

Table B.2: The value of labor market specific work experience

Dependent variable: logarithmic wages in new employment relationships

	(1)	(2)	(3)
Experience Berlin / Hamburg / Munich	0.003^{***}	0.006^{***}	0.013^{***}
	(0.000)	(0.002)	(0.002)
Experience Berlin / Hamburg / Munich $\times$ experience †			-0.005^{***}
			(0.000)
Experience	0.015^{***}	0.033^{***}	0.065^{***}
	(0.000)	(0.001)	(0.001)
$(\text{Experience})^2$			-0.001^{***}
			(0.000)
Experience Berlin / Hamburg / Munich, now elsewhere †	0.059^{***}	0.007	0.020
	(0.006)	(0.006)	(0.016)
Experience Berlin / Hamburg / Munich $\times$ experience, now elsewhere †			0.001
			(0.001)
Experience outside Berlin / Hamburg / Munich , now in 3 largest	0.007^{***}	0.001^{**}	0.007^{***}
	(0.000)	(0.001)	(0.002)
Experience outside Berlin / Hamburg / Munich $\times$ experience, now in 3 largest †			-0.003^{***}
			(0.001)
New employment relationships	336,286	336,286	336,286
OLS: R^2, FE: within R^2	0.613	0.180	0.191
Worker fixed effects	No	Yes	Yes

† Coefficient and standard error multiplied by 10.
Note: Robust standard errors are given in parentheses which are clustered by worker. ***, ** and * indicate significance at the 1, 5 and 10 percent level. Work experience measured on a daily bases and expressed in years. All models include control variables as well as year, industry, occupation, and region fixed effects (see Table B.1).
Source: IEB V11.00.00 – 131009, own calculations.

B.3 The portability of accumulated human capital

In the main part of this paper we assume that the value of work experience as reflected in wages is exclusively determined by characteristics of the local labor market in which it was acquired, and not by the labor market in which it is used. This assumption is relaxed

[f] The estimated earnings premia are only to a limited extent comparable across countries as the largest local labor markets within the different countries and also the respective reference, i.e., the country specific 'average' local labor market differ in size.

below.[g] One reasonable explanation as to why the size of the labor market in which experience is used might impact on work experience's value is matching advantages in large labor markets. The latter might imply that previously accumulated human capital can more efficiently be used in the new job the larger the labor market is in which the new employer is located. Therefore, Equation (B.2) contains an interaction effect of the (cumulated) size of the labor markets in which experience was acquired and of the (logarithmic) size of the labor market in which the experience is used, $emp_{r(i,t),t}$. In order to impose the restriction that the (unknown) threshold beyond which valuable experience is acquired, $\underline{emp}$, is supposed to be independent of the labor market in which experience is used, we estimate this threshold in this specification explicitly and not γ which is defined as $-\delta \ln(\underline{emp})$ (compare Equation 4).

$$\begin{aligned} w_{i,t} \;=\;& u_i + \mu_{r(i,t),y(t)} + \delta \sum_{\tau=1}^{t-1} (1-\theta)^{t-\tau-1} I(O_{i,\tau}=1) \ln \frac{emp_{r(i,\tau),\tau}}{\underline{emp}} + \\ &+ \delta' \left\{ \sum_{\tau=1}^{t-1} (1-\theta)^{t-\tau-1} I(O_{i,\tau}=1) \ln \frac{emp_{r(i,\tau),\tau}}{\underline{emp}} \right\} \ln(emp_{r(i,t),t}) + \\ &+ \mathbf{x}'_{i,t}\beta + \varepsilon_{i,t} \end{aligned} \tag{B.2}$$

We divided $emp_{r(i,t),t}$ by its mean. Because of this transformation, δ denotes in this specification the elasticity of wage with regard to the size of the labor markets in which experience was acquired *given* the experience is used in a labor market with a workforce of about 179 thousand employees, the mean of regional employment in Germany. $\delta' \ln(n)$ is the (absolute) change in this elasticity if the experience is used in a labor market that is, instead, n-times as large as the average regional labor market.

The results in Columns (1) and (2) of Table B.3 show that δ' is very precisely estimated, the coefficient is statistically highly significantly different from zero. However, the magnitude of this interaction effect is economically very small. If work experience is used in a labor market with a local workforce of, e.g., 50 thousand employees, $\hat{\delta} + \hat{\delta}' \ln(50,000/171,000)$ is, according to the results in column (1) [column (2)], 0.204×10^{-4} [0.185×10^{-4}]. If experience is used in a labor market with a local employment of one million workers, $\hat{\delta} + \hat{\delta}' \ln(1,000,000/171,000)$ is 0.214×10^{-4} [0.214×10^{-4}]. It means that the elasticity of wage with regard to the size of the labor markets in which experience was acquired varies at most slightly in dependence of the size of the labor market in which experience is used.

This conclusion is supported by the results reported in Columns (3) and (4). They refer to Equation B.3. In this regression model δ is again allowed to vary depending on the (type of) region in which the experience is used. More precisely, we now distinguish whether the new employer is located in a small, medium, or large labor market. As large local labor markets we consider those with a local workforce of more than 750,000 employees: Berlin, Hamburg, Munich, Frankfurt, Düsseldorf, Stuttgart, Cologne. Labor markets with less than

[g] As in the baseline specifications, we use the local labor market size in terms of total regional employment in order to quantify dynamic agglomeration gains. We do not distinguish whether the benefit from acquiring experience in a large labor market is related to the large number of workers or the above average share of high-skilled labor.

100,000 employees are considered as small labor markets, i.e., 43 percent of all German local labor market regions. The remaining labor markets represent the reference group.[h]

$$w_{i,t} = u_i + \mu_{r(i,t),y(t)} + \delta_{r(i,t)} \sum_{\tau=1}^{t-1} (1-\theta)^{t-\tau-1} I(O_{i,\tau}=1) \ln \frac{emp_{r(i,\tau),\tau}}{\underline{emp}} + \mathbf{x}'_{i,t}\beta + \varepsilon_{i,t} \quad \text{(B.3)}$$

Based on the results in Column (3), the null hypotheses *'Wages in the large and the small labor markets, respectively, are as elastic with regard to the size of the labor markets in which experience was acquired as in the medium size labor markets'* cannot be rejected at conventional levels. According to the results in Column (2), δ_l is statistically larger than δ_m. However, economically the difference in the elasticities is again small.

Table B.3: Estimates of the parameters of the learning function depending on the size of the labor market in which experience is used

	(1)	(2)	(3)	(4)
$\hat{\delta}$ †	0.208***	0.198***		
	(0.004)	(0.006)		
$\hat{\delta}'$ †	0.003***	0.010***		
	(0.001)	(0.002)		
$\hat{\delta}_m$ †			0.215***	0.208***
			(0.004)	(0.006)
$\hat{\delta}_l$ - $\hat{\delta}_m$ †			0.003	0.014***
			(0.003)	(0.005)
$\hat{\delta}_s$ - $\hat{\delta}_m$ †			−0.001	−0.007
			(0.003)	(0.006)
$\widehat{\underline{emp}}$	15.229	23.356	20.247	36.218
	(14.937)	(29.273)	(18.624)	(40.888)
$\hat{\theta}$ †	3.452***	4.373***	3.402***	4.158***
	(0.153)	(0.291)	(0.152)	(0.281)
New employment relationships	336,286	214,319	336,286	214,319
within R^2	0.197	0.261	0.197	0.261

† Coefficients and standard errors multiplied by 10,000.
Note: Robust standard errors are given in parentheses which are clustered by worker. ***, ** and * indicate significance at the 1, 5 and 10 percent level. δ is allowed to vary across three groups of labor markets in which previously acquired word experience is used. Columns (1) and (2) refer to Equation (B.2), Columns (3) and (4) to Equation (B.3). In the latter specifications subscript l indicates that previously acquired word experience is used in a *large* local labor market with a total number of at least 750,000 employees. Subscript s refers to *small* regional labor markets with less than 100,000 employees, and m to the reference group, i.e., *medium* size labor markets. The results reported in Columns (1) and (3) are obtained using the full sample, those in Columns (2) and (4) using a reduced sample which does not contain new employment relationships of workers who acquired experience before 1995. All models including control variables as well as worker, industry, occupation, and region-year fixed effects (see Table B.1).
Source: IEB V11.00.00 – 131009, own calculations.

Overall the results in Table B.3 show similar to the results reported in Table B.2 and by De La Roca/Puga (2017) that the value of experience varies at most little between labor markets that differ in size. Hence, these results indicate that the value of work experience is (predominately) determined by the size of the labor market in which it was acquired and varies only little if workers move to an other labor market that differs in size. It also means that a worker who previously worked in a large labor market is in comparison to a worker who previously worked in a small local labor market, ceteris paribus, more productive, in-

[h] We also estimated specification where we require large labor markets to have a local workforce of at least 500,000 employees and at least 1,000,000 employees, respectively. The obtained results are very similar to those reported in Table B.3 and available upon request.

dependently of where they make use of their work experience. This finding also supports the hypothesis that the identified dynamic agglomeration gains are related to learning externalities.

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